DNSC 6279 - Data Mining - Project Report

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1 Problem Statement

Github (github.com) is a popular social network for software developers and the code they produce. It allows individual programmers and groups or organizations to publish and share their code using the Git version control software application, and it enables powerful features for sharing changes to code. Many of the world's most widely used software products are shared on Github, such as the Linux kernel, and even projects that aren't actively developed using Github mirror their code to Github for the benefits of visiblity and ease of use Github offers, including the Apache web server, the Python programming language, the PostgreSQL database, and Git itself. By a rough count (using the monotonically-increasing "id" variable present in API calls to list repositories registered in Github, more about which below), there have been well over nineteen million software project repositories registered in Github since its inception in early 2008. In my own work at GW and within my industry (software development in libraries) I and most of my colleagues perform the majority of our work using Github, so I have a strong personal interest in its success as a platform and what we may learn from it.

One of the hardest choicest to make as a software developer – especially as one who works with free/libre/open source software often, as I and my colleagues do – is which software projects and products written by other people we should use as a basis upon which to build our own software. For any common computing problem there are at least three different packages available in any programming language of choice, so which is the best to use? Which packages work best, and which new initiatives are likely to "get traction"? There is a natural tension between doing new work in software and building that new work upon other, existing, reliable packages, to narrow the scope of innovation and to allow for a stable development environment. Because of this software developers have a natural tendency to look for certain things when evaluating a package: Who is its author? How long has it been under development, and how active has its development been lately? Does the community use tickets and milestones to plan releases? Have others "forked" the package (made their own copy) and submitted their own changes to it? No one answer to these questions is a perfect piece of information, rather we go on intuition and experience to make these choices.

The Github API (developer.github.com/v3/) provides an opportunity to examine these choices, and to determine whether we can predict the potential success of a software project using data rather than simply by intuition. For each repository in Github, extensive metadata about that repository and its activity is available through a well-documented set of API calls. For this project, I collected this metadata for roughly 10,000 repositories registered between 2008-2010, and I attempted to build several models that might tell us more about what we can determine automatically about any repository in Github, based on how the project is managed in Github, the programming language choices its authors make, and patterns of recent development activity for each project. Although I do not have a great deal of confidence in these models, the process has taught me a lot about the data mining process, especially the critical data collection and pre-processing steps, and also about Github as a community.

2 Data Selection

I used the following calls to Github's API to return data for each repository. Note that each URL begins with "https://api.github.com". These API calls are documented extensively on the Github API site.

Path	Description
/repositories	A pageable list of repositories, starting from oldest
/repos/owner/name	Basic metadata (owner, name from previous call)
/repos/owner/name/contributors	Pageable details about all code contributors
/repos/owner/name/stats/participation	Counts of commits by owner vs. all others, past year
/repos/owner/name/languages	Relative size of code by programming language
/repos/owner/name/stats/code_frequency	Counts of lines added/removed weekly, past year

These calls generated a lot of raw data for each repository which I then processed further, as described in Section 3 below. For each repository, basic metadata of value for this project includes:

Field	Description	Type
id	unique identifier	int
owner	repository owning user	string
name	repository name	string
created_at	date of repository creation	date
pushed_at	date of last “pushed” commit (change)	date
fork	whether this is a “fork” or copy of another repository	boolean
forks_count	number of forks of this repository	int
has_wiki	whether the project uses Github’s wiki pages	boolean
has_issues	whether the project uses Github’s issue tracking	boolean
has_downloads	whether the project has downloadable package builds	boolean
parent_id	id of project from which this project was forked, if applicable	int
source_id	id of original project from which this and parents were forked	int
size	size of the repository, in source lines of code	int
open_issues_count	number of currently-open issues in Github’s issue tracker	int
stargazers_count	# users who have “starred” (or favorited) this repository	int
subscribers_count	# users who subscribe to update notifications	int
network_count	number of all forks in network of source repository	int

For this project, I used “id” as an identifier variable, “stargazers_count” as the target variable, and rejected “owner” and “name” although I carried them through into SAS as useful metadata to check values against (we can easily construct a Github URL to a repository if we have its owner and name).

Further details about processed variables are specified in the next section.

Before continuing, however, a few details about the process of fetching data from the API are worth noting. Collecting the data from Github proved to be more of a challenge than I expected for several reasons:

- Github limits API calls to 5000/hour, so at the rate of six calls per repository, it took several overnight runs to collect full data for over 10,000 repositories (and re-runs after adjusting the code several times).

- The fetch script I wrote honors this limit by attempting to wait between calls according to the amount of time remaining before the wait limit is reset by the API, but I found that this reset time was sliding backwards, causing my code to issue calls after a longer delay than necessary. After testing this very carefully I wrote to Github staff about it, and reported it as a bug with details about my queries. They acknowledged it was a bug in their system and thanked me for the report, but as far as I know the problem has not yet been fixed. I estimate this slowed down my data collection by 30-40%.

- Some of the API calls (specifically the ones that include ’/stats’ in the URL pattern) are documented as “slow” on the API side as they calculate summary statistics. These calls might result in an HTTP response code 202 Accepted (rather than 200 OK) which indicates that the request has been acknowledged but the response is not yet ready. To accomodate this possibility, which I saw regularly as my fetch script executed, I implemented a simple linear backoff strategy to enable subsequent calls with an increasing delay between each call. This strategy worked, but it also slowed down the data fetching process.

- Some registered repositories have no meaningful data within them; I chose to ignore these, and did not include them in the sample.
- Some API calls (e.g. /stats/contributors) require paging to fetch all results; I used /contributors instead to save time, but only after first fetching the more complete details, which did not prove interesting after all.
- Sometimes my script simply failed (due to bad logic or improper error handling in my code, failed network connection, etc.). At first, I had to restart it over from scratch, but after losing data a few times I wrote an "append" feature that attempts to discover where the process last left off by checking the id of the last repository in the most recently saved file (the fetch scripts saves data in chunks of 100 repositories per file).
- After working with the results of metadata about several thousand repositories, I noticed an obvious trend I should have considered sooner. The API call to list all the repositories in Github started back at the beginning of Github, and proceeded chronological order. Because of this, I was only retrieving data about the very oldest data in Github. This seemed like a strong bias to use as the community of users for Github started small, like for any social network, and grew first from a set of users who had particular interests in the same languages and tools the Github developers themselves used. Indeed the most active early users were the founders of Github themselves, and some of the earliest repositories were Ruby-based web applications (Github is a Ruby language application) and Ruby-based libraries for working with Git repositories. Rather than proceed with this bias, I added a "striping" function to the fetch script to jump ahead in time between calls. With the response to the query returning 100 repositories, I modified the next call to the API to jump ahead 9900 repositories, thus taking a sample of 100 out of each 10,000 in chronological time, or 1% of repositories overall. Without this change, my sample set would have only contained the oldest repositories from the first few months of Github's existence; instead, it includes a sampling of repositories from the first three years. This still exhibits a bias of sorts as Github's largest growth has come in the past 2-3 years, but this still seemed to be a good enough sample for this project. Perhaps I will follow up with exploring a larger sample including more recent repositories in the future.

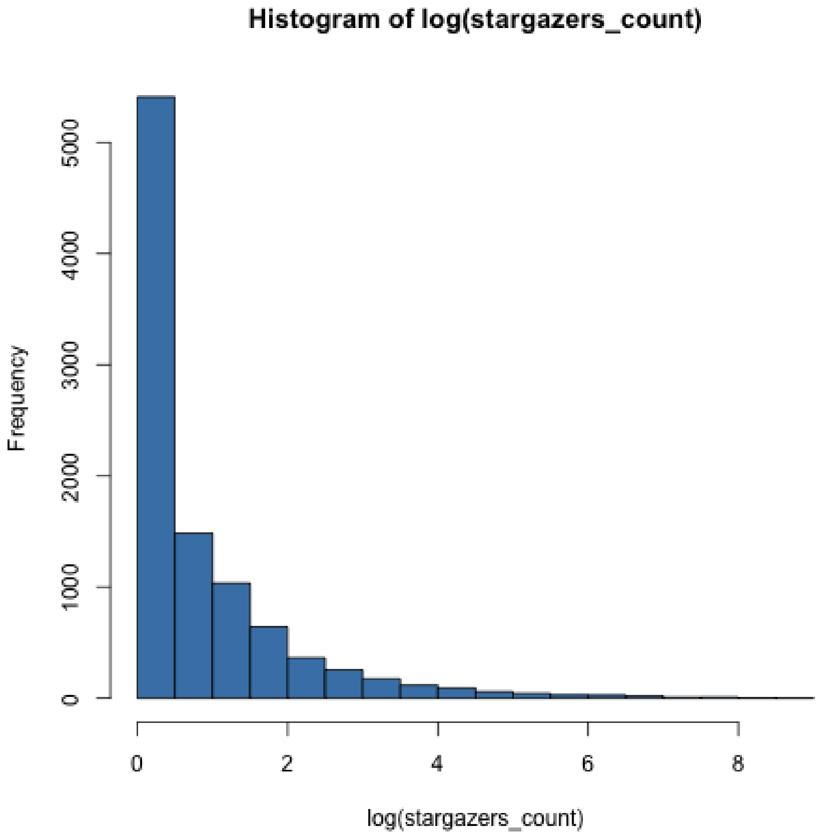
This set of issues led to a longer period of iteration over the data fetching process, delaying the processing and modeling steps. It reinforced a key lesson, that there is no such thing as "clean data", even if it's coming from a "clean API". Every API has its own quirks, and possibly flaws, and it will always take time to account for and adjust to these issues.

3 Data Pre-Processing

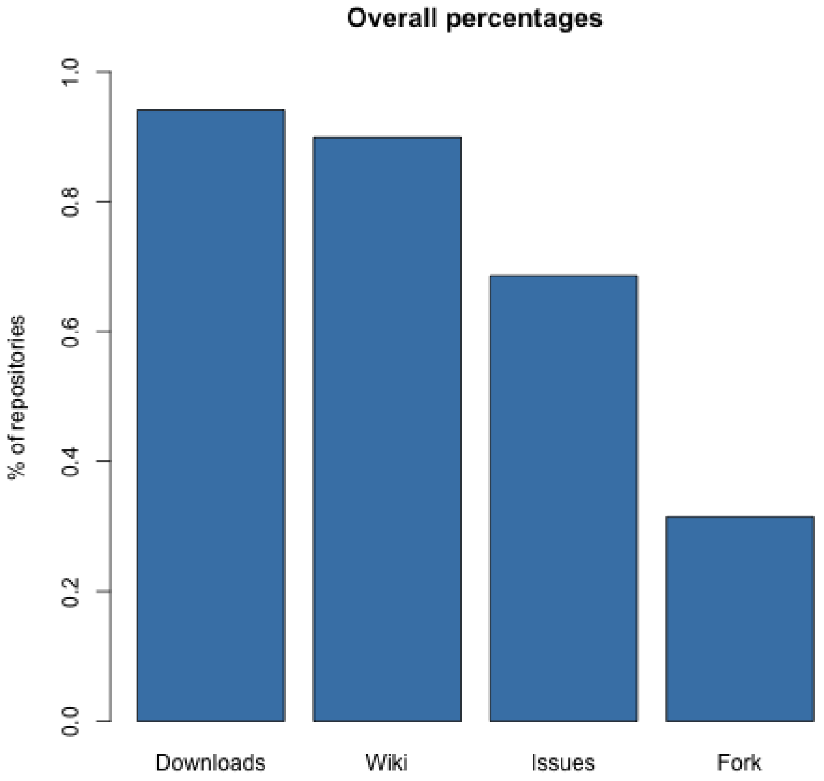
What operations did you perform on your data to organize it in a form suitable for Enterprise Miner. Specify any queries, joins, transformations, how you treat missing values etc.

I collected the data from the Github API into a set of JSON files, 100 records per file, for a total of n=10,096 repositories. For each repository record, I started with the basic JSON-based response to the basic metadata request for each repository and added results from the additional calls to the in-memory dictionary for each respository before writing each to local disk. JSON is an excellent format for this kind of work; it has all the hierarchical expressiveness of XML but very little overhead, and it takes exactly one line to either read it in or write it out from most languages.

The overall set of data I chose included a wide variety of potential values. It seemed best to explore it some and determine how best to pre-process one or more files for import into SAS prior to model building. Here are some of the basic impressions the data gave at first glance.

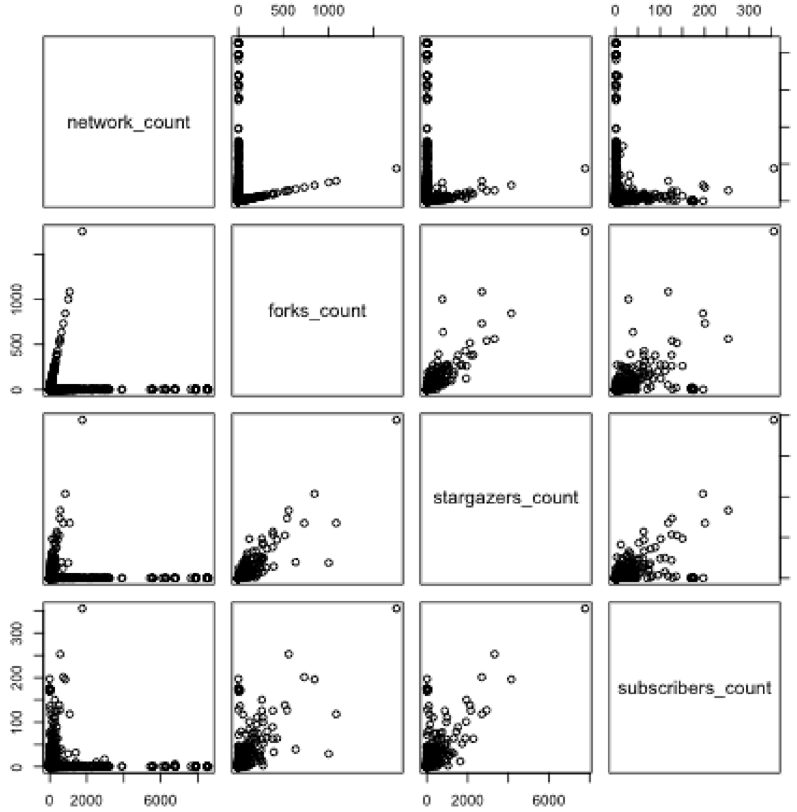


Starting with the dependent/target variable “stargazers_count”, we see that it has a lognormal distribution evidenced by the histogram of the log of this value. A small proportion of repositories among the over ten thousand I collected ever “caught on”.



I suspected that projects that made use of Github’s issue tracking feature might be more popular because this indicates that the community of developers is actively working on the code and soliciting feedback. Similarly, but to a lesser extent, I suspected that use of other Github features such as their “file downloads” feature and project wiki pages might also indicate project health. The numbers for Downloads and Wiki seem unusually high to me, though, and although I’ve verified that this is what the data I fetched indicates, this does not seem to correspond to what I’ve seen in project sites, in particular it seems like far fewer than 90% of projects use the downloads feature, but this indicates the percentage is higher than 90%. Perhaps these values are not trustworthy. The lower number for Issues is perhaps more likely to be accurate, and the final bar for Fork, indicating that roughly 30% of repositories are forks of other repositories, seems plausible enough, although I am unexcited about its potential predictive value.

Another exploratory chart indicates a strong relationship between forks and stargazers:



Here we can see that there is indeed a strong correlation between the number of stargazers and the number of forks of a project. This makes intuitive sense; more popular projects seem more likely to find other users working with the code, offering up changes, etc.

At this point it seemed clear that there might not be any groundbreaking paradigm to discover here; a log/power tail of projects are popular, popular projects get forked a lot, and some of the data from the API might not be 100% reliable (based on the percentages of repositories that use downloads and wikis). It seemed like a good idea to start to derive new attributes from the existing data.

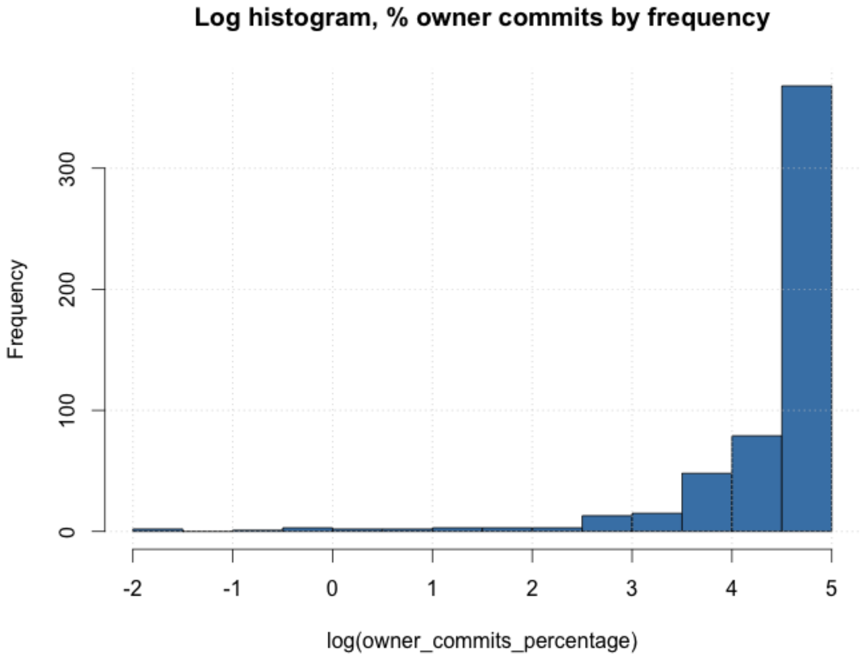
I decided to break the data down along three lines: basic attributes, code activity, and languages. The basic attributes are those already defined and listed in the previous section. To this I added the following set of computed values based on activity on the repository:

’star10’, ’lang0_prop’, ’lang0’, ’lang1’, ’lang2’,

Field	Description
num_contributors	count of distinct users contributing code
num_weeks	weeks since project inception
num_weeks_since_change	weeks since last commit
lines_added	total lines added, past year
lines_added_per_week	avg lines added/week, past year
lines_subtracted	total lines subtracted, past year
lines_subtracted_per_week	avg lines subtracted/week, past year
all_commits	total count of commits
owner_commits	commits by owner, past year
owner_commits_percentage	percent of commits by owner, past year
mean_commits_per_week	mean commits/week, past year
std_commits_per_week	standard dev. of commits/week, past year

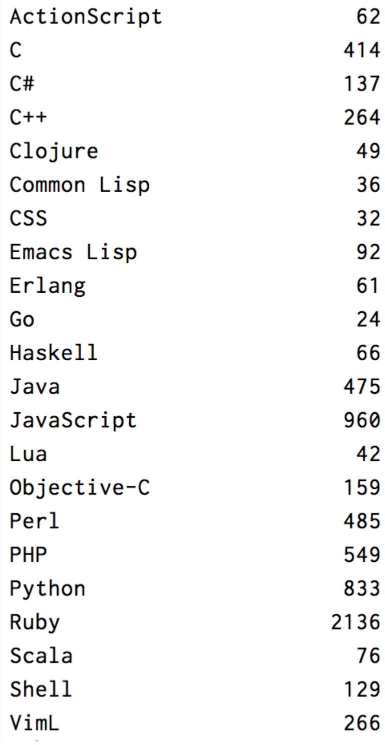
These values were readily obtained and computed from the API data provided, implemented in the script “process.py” (see Appendix).

As an example of these attributes, below is a chart of owner_commits_percentage, indicating how many changes to each repository in the past year had been commited specifically by the repository owner themself:



The vast majority of projects active in the past year had a majority of its commits in the past year created by the repository owner (the two bins at the far right with log(owner_commits_percentage > four). This indicates that a very small minority of projects have a plurality of active committers.

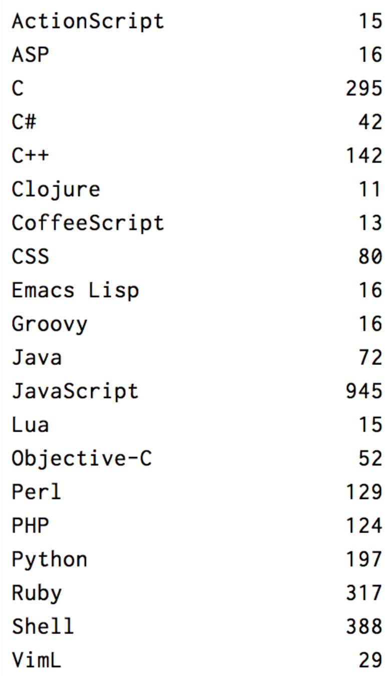
The last area of repository composition I reviewed was the choice of languages used in each project. I was interested to see if there was any pattern present across several years of Github data toward a preference for particular languages, or whether these matched language popularity in the wider community. Summarizing the languages used in repositories by the top two per each (more than one kind of language can be used in a single project, and often is) revealed the following basic data:



```
ActionScript              62
C                        414
C#                       137
C++                      264
Clojure                   49
Common Lisp               36
CSS                       32
Emacs Lisp                92
Erlang                    61
Go                        24
Haskell                   66
Java                     475
JavaScript               960
Lua                       42
Objective-C              159
Perl                     485
PHP                      549
Python                   833
Ruby                    2136
Scala                     76
Shell                    129
VimL                     266
```

Note that Ruby is the most popular primary language, followed by JavaScript, Python, Java, PHP, Perl, and C. This is not a surprising list when compared to industry measures of the same information (for example, see http://www.tiobe.com/index.php/tiobe_index) and accounting for the early prevalence of Ruby code in Github's early days.

The most-used secondary languages are slightly more interesting:



```
ActionScript              15
ASP                       16
C                        295
C#                        42
C++                      142
Clojure                   11
CoffeeScript              13
CSS                       80
Emacs Lisp                16
Groovy                    16
Java                      72
JavaScript               945
Lua                       15
Objective-C               52
Perl                     129
PHP                      124
Python                   197
Ruby                     317
Shell                    388
VimL                      29
```

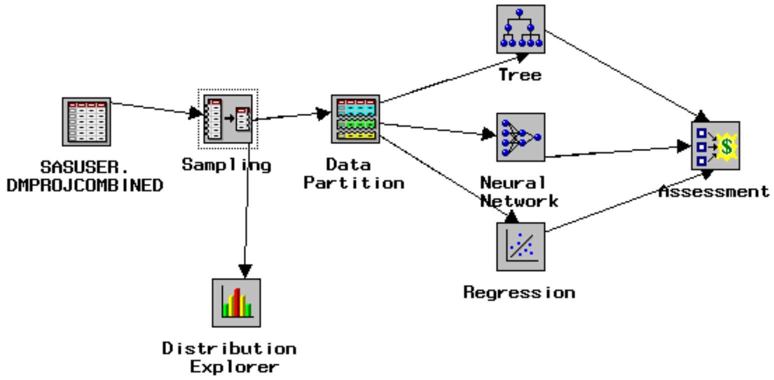
In this list the most popular secondary languages in projects was JavaScript, by far, followed by Shell, Ruby, C, Python, and C++. This makes an intuitive sense as many projects in Github are web and mobile applications, and many of these applications use at least some JavaScript, whether the larger application itself is written in Ruby, Python, PHP, or any other language. Shell is a common choice for tool scripts around the main code of a project, with Unix commands written in Shell to automate tasks related to application configuration, data management, backups, and other maintenance tasks.

One final attribute I computed was "star10", a binary classification of whether a repository had at least ten stargazers. This proved to be useful in generating stratified samples as well as being a target variable for model generation, as described in the next section.

4 Mining Technique Selection

I chose to work with a Regression, Neural Network, and a Classification Tree for this model, as each can be used to create predictive models. At first I worked with one combined dataset and used stargazers_count as the target variable. This resulted in unexciting models that did not reveal much, largely due to the log distribution of popularity present in stargazers_count, as shown above in the histogram of log(stargazers_count).

I consulted with Professor Prasad who encouraged me to take a stratified sample to capture the "rare event" of popularity according to stargazers_count. I added a Sampling node in SAS and found that it was easiest to generate an additional binary attribute “star10”, based on whether a repository had at least 10 stargazers, to use as the stratification attribute. I created a 2000-item sample using a 50/50 equal sized stratification in slotted that between the Data Source and Partition nodes, using an 80%/20% training/validation split. I then fed that to one each of Tree, Neural Network, and Regression models, finally drawing each of those into an Assessment node. The diagram in Enterprise Miner is the following:



This represents the final model I will describe in detail now. One quick note, however: before combining all the data into one data source, I attempted to separate out the three categories of attributes mentioned above into their own datasources for basic metadata, project activity, and language choices, running the three models paradigms separately on each. This did not prove fruitful, save for one mildly interesting finding. Upon running the neural network on language choice data, it drew out “lang1 = JavaScript” as a modest predictor of project popularity. As noted in the previous section, JavaScript is a prevalent secondary language in repositories of many languages, in particular for web and mobile applications. This is not particularly meaningful in the large picture beyond keeping in mind that “web and mobile applications are popular”.

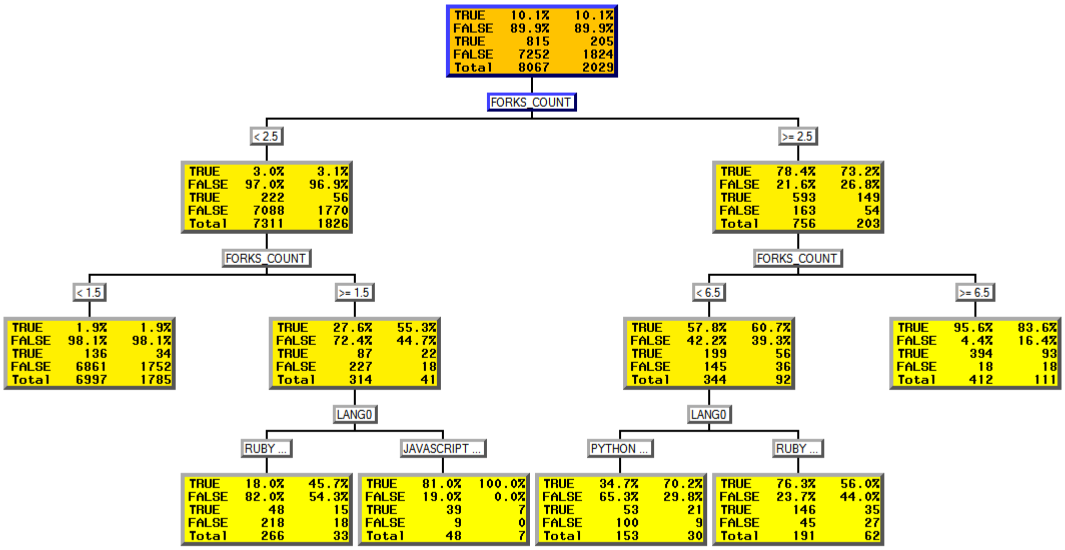
For all of these models, I began using the “stargazers_count”, an interval attribute, as the target/dependent variable. This provide largely difficult to predict well, and none of the models were able to come close to a reliable prediction. Having derived the new attribute “star10”, a binary classification of whether a repository had at least 10 stargazers, to use as a parameter to stratify the sample upon, I tried using star10 as the target instead of stargazers_count, thinking it might simplify the problem somewhat. After all, whether a project has 12 or 22 stargazers or whether it has 500 or 600 doesn’t seem terribly important; that it has at least 10 indicates some basic level of user interest. This proved to be an improvement, as the models all generated somewhat better results, if not still overwhelmingly so.

In all of the following discussion, “star10” is the target variable.

5 Data Mining Results

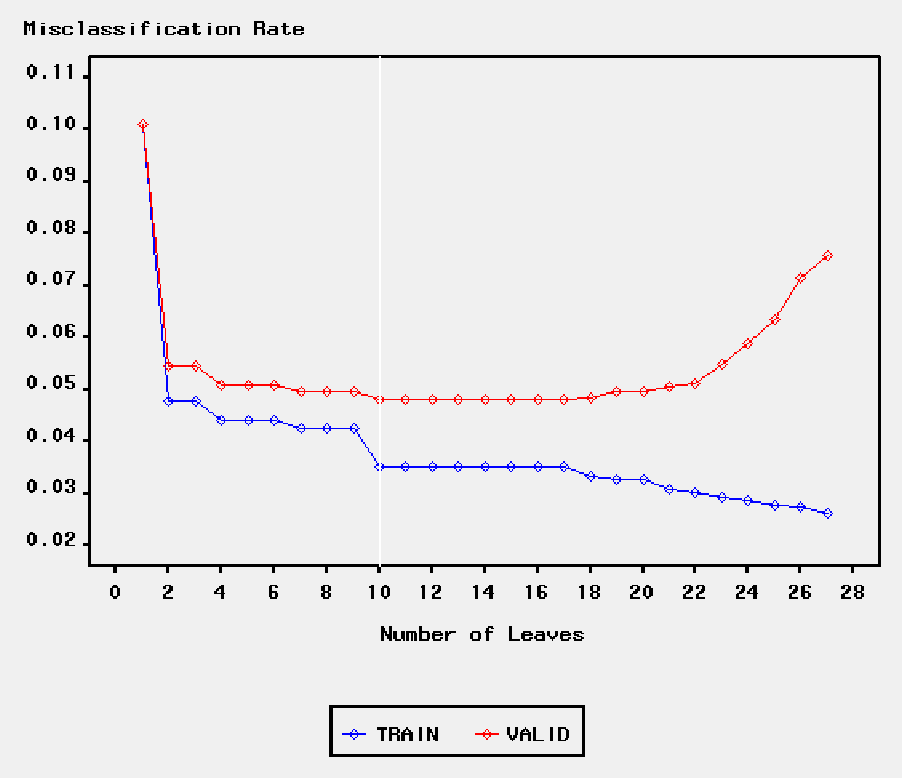
5.1 Classification Tree

For the Tree model, I used the Gini reduction splitting criterion and allowed SAS to select the model assessment measure by setting it to "automatic", and left other settings to their defaults. It produced a tree that focused primarily on the forks_count attribute, noted above as a value apparently linearly correlated with project popularity. Below is the tree:



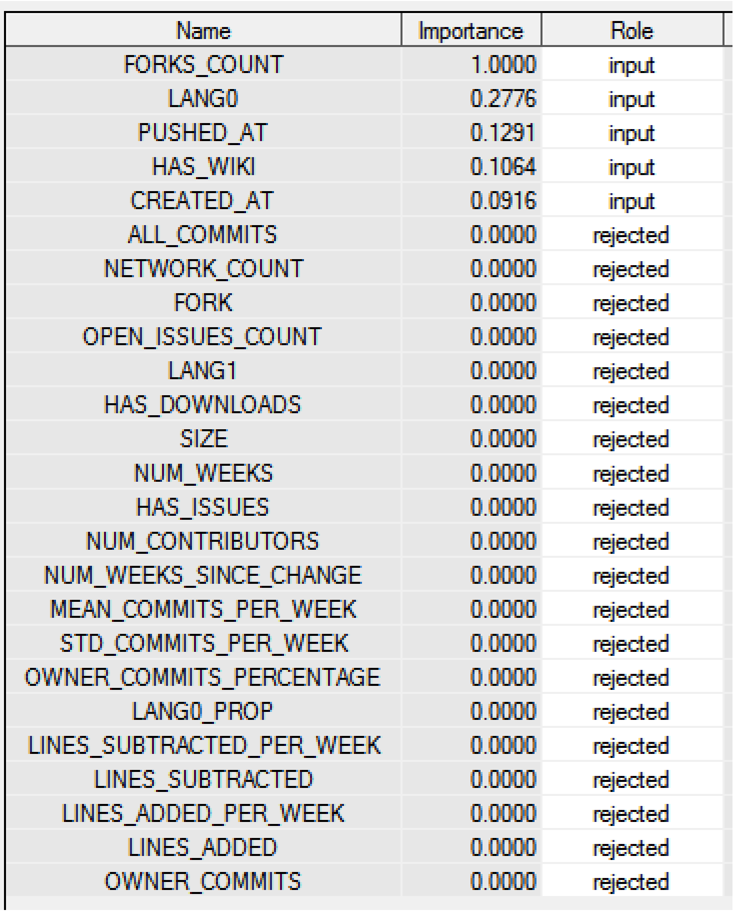
This tree follows simple rules: if there are more than two forks, the project is typically at least modestly successful; if there are less than two, it probably isn't. At both of these ends of the spectrum, the validation data results are quite close to the training results. In the case of zero or one fork, the model correctly predicted roughly 1.9% of items as "popular"; for 3-6 forks, the validation rate of 60.7% is close to the training rate of 57.8%, and for more than seven forks, from 95.6% (training) to 83.6% (validation) isn't terrible. In between these values, particularly for repositories with exactly two forks, the validation results are poor. The lowest-level split on "lang0" does not add a lot to the picture.

The misclassification rates per number of leaves shows a classic set of rate curves, with the U-shape of the validation results looking strong.



This reinforces what we learned about the interpretability of a simple classification tree. The splits on forks_count are intuitive and match my expectations as noted above. Anyone looking at the model can quickly understand that either a low or modestly high forks_count on a repository is a good indicator of what to expect. Ultimately, the takeaway lesson that if you see that at least three different people have forked a repository, it probably has at least ten people watching it, and is thus “popular” in some sense, is a decent rule of thumb that is easy to remember. The corollary that a project with only zero or one fork is unlikely to be successful yet is also intuitive and easy to remember.

One final observation: the SAS tree model only found a handful of attributes even worth considering beyond forks_count and lang0, as indicated in this table:

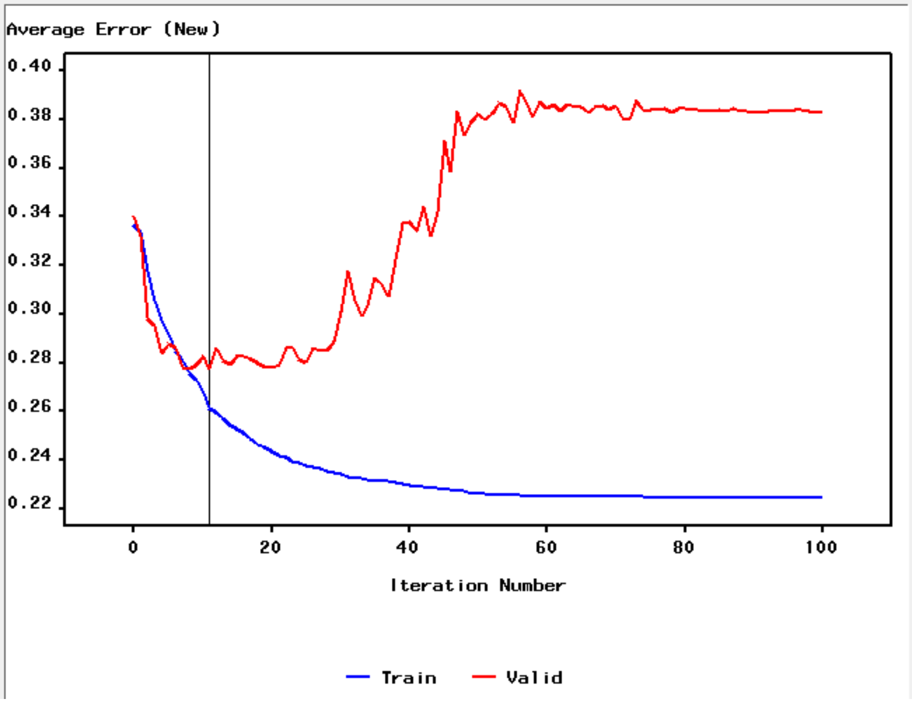


Name	Importance	Role
FORKS_COUNT	1.0000	input
LANG0	0.2776	input
PUSHED_AT	0.1291	input
HAS_WIKI	0.1064	input
CREATED_AT	0.0916	input
ALL_COMMITS	0.0000	rejected
NETWORK_COUNT	0.0000	rejected
FORK	0.0000	rejected
OPEN_ISSUES_COUNT	0.0000	rejected
LANG1	0.0000	rejected
HAS_DOWNLOADS	0.0000	rejected
SIZE	0.0000	rejected
NUM_WEEKS	0.0000	rejected
HAS_ISSUES	0.0000	rejected
NUM_CONTRIBUTORS	0.0000	rejected
NUM_WEEKS_SINCE_CHANGE	0.0000	rejected
MEAN_COMMITS_PER_WEEK	0.0000	rejected
STD_COMMITS_PER_WEEK	0.0000	rejected
OWNER_COMMITS_PERCENTAGE	0.0000	rejected
LANG0_PROP	0.0000	rejected
LINES_SUBTRACTED_PER_WEEK	0.0000	rejected
LINES_SUBTRACTED	0.0000	rejected
LINES_ADDED_PER_WEEK	0.0000	rejected
LINES_ADDED	0.0000	rejected
OWNER_COMMITS	0.0000	rejected

Among these attributes, only lang0 from among all the language-related attributes, and only pushed_at from among the attributes indicating project activity, were deemed at all important. Even these were found to be of very low importance, on a par with has_wiki (discounted due to perceived unreliability in discussion above) and created_at, which might bring a component of bias for the older and oldest projects, which have simply had more time to be "starred", especially in the early days when very few repositories had even been registered yet.

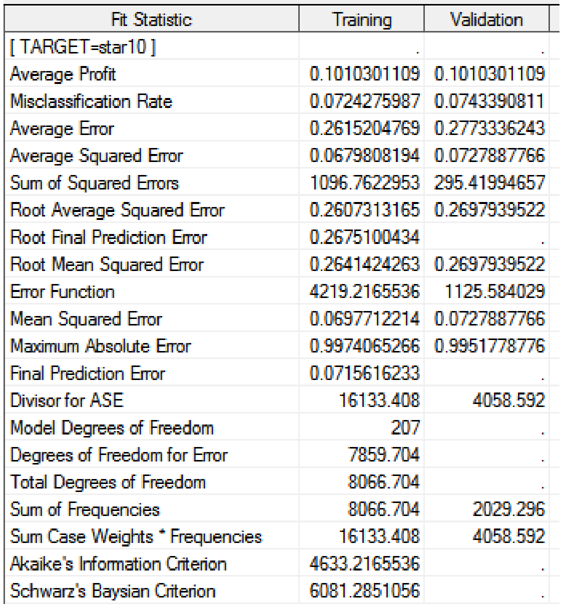
5.2 Neural Network

For the neural network I used a Multilayer Perceptron with misclassification rate as the model selection criteria. Knowing that a neural network is at the opposite end of the interpretability spectrum, let's start with the average error chart:



The model performs fairly well after a few iterations but plateaus after around 10 and then degrades as we might expect after 30 or so iterations. A look at the cumulative lift chart reveals some improvements:

Here are the fit statistics for the neural network:



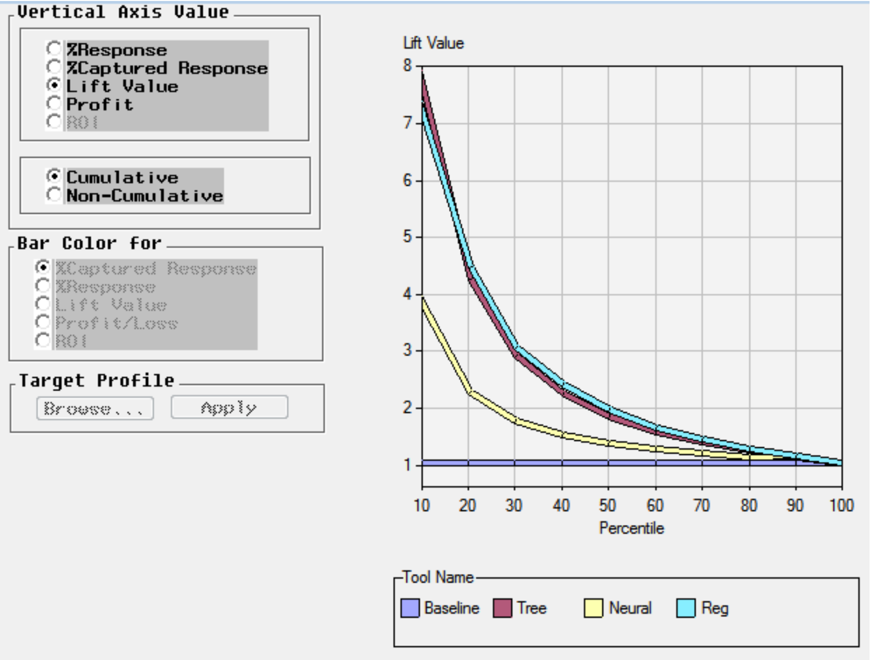
Fit Statistic	Training	Validation
[TARGET=star10]	.	.
Average Profit	0.1010301109	0.1010301109
Misclassification Rate	0.0724275987	0.0743390811
Average Error	0.2615204769	0.2773336243
Average Squared Error	0.0679808194	0.0727887766
Sum of Squared Errors	1096.7622953	295.41994657
Root Average Squared Error	0.2607313165	0.2697939522
Root Final Prediction Error	0.2675100434	.
Root Mean Squared Error	0.2641424263	0.2697939522
Error Function	4219.2165536	1125.584029
Mean Squared Error	0.0697712214	0.0727887766
Maximum Absolute Error	0.9974065266	0.9951778776
Final Prediction Error	0.0715616233	.
Divisor for ASE	16133.408	4058.592
Model Degrees of Freedom	207	.
Degrees of Freedom for Error	7859.704	.
Total Degrees of Freedom	8066.704	.
Sum of Frequencies	8066.704	2029.296
Sum Case Weights * Frequencies	16133.408	4058.592
Akaike's Information Criterion	4633.2165536	.
Schwarz's Baysian Criterion	6081.2851056	.

We see that the RMSE increases from 0.264 (training) to 0.27 (validation), a modest change that indicates that the model might do a decent job with predicting. The misclassification rate goes from 0.072 (training) to 0.074 (validation), also a modest change.

5.3 Regression

5.4 Comparison

A look at the combined lift charts reveals no clear winner but a definite loser: the regression and tree models work pretty well, but the network does not perform as well. Here is the combined chart of cumulative lift:



Vertical Axis Value

○ %Response
○ %Captured Response
● Lift Value
○ Profit
○ ROI

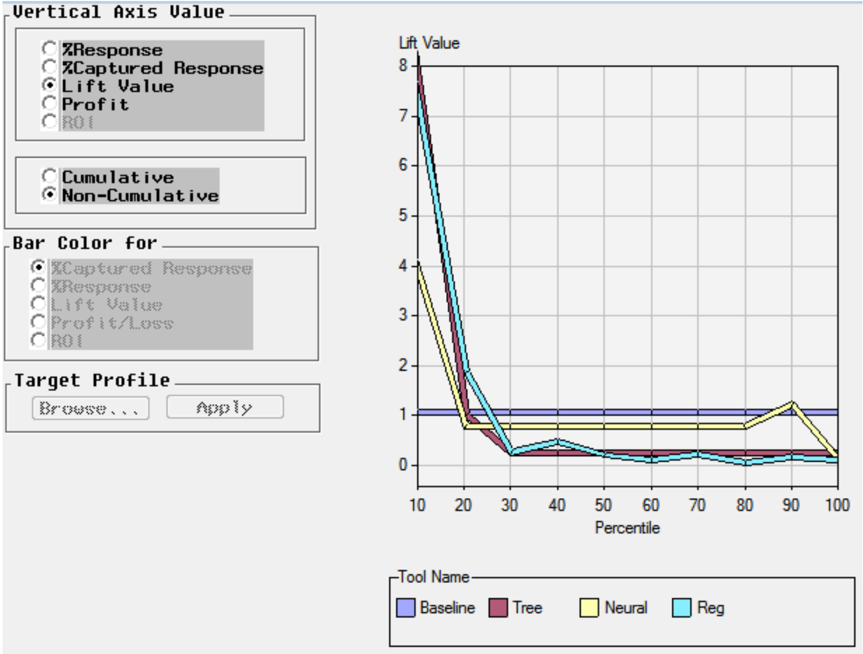
● Cumulative
○ Non-Cumulative

Bar Color for

● %Captured Response
○ %Response
○ Lift Value
○ Profit/Loss
○ ROI

Target Profile

Here we see that the tree model performs best, with a lift close to 8 in the first decile; the regression model performs nearly as well, still above 7, and the neural network model offers up a modest improvement at a lift of just under 4. At the second decile and beyond the regression model appears to outperform the tree model slightly. A closer look at the noncumulative lift is below:



Vertical Axis Value

○ %Response
○ %Captured Response
● Lift Value
○ Profit
○ ROI

○ Cumulative
● Non-Cumulative

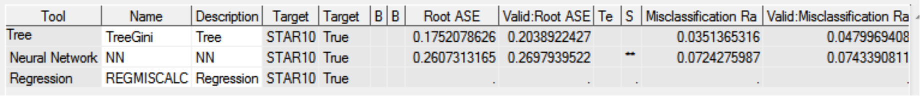
Bar Color for

● %Captured Response
○ %Response
○ Lift Value
○ Profit/Loss
○ ROI

Target Profile

In this chart the slightly higher slope of the regression model to a positive lift at the 20% decile is evident over the more quickly degrading lift of the tree model, but they are both offer only marginal results beyond the 10% decile. An interesting hiccup is the gentle spike at 90% for the neural network; perhaps it has some capacity to correctly determine low-end "not popular" classifications, even if this is not useful.

We can compare the tree and network models another way, using their misclassification rates:



Tool	Name	Description	Target	Target	B	B	Root ASE	Valid:Root ASE	Te	S	Misclassification Ra	Valid:Misclassification Ra
Tree	TreeGini	Tree	STAR10	True			0.1752078626	0.2038922427			0.0351365316	0.0479969408
Neural Network	NN	NN	STAR10	True			0.2607313165	0.2697939522		**	0.0724275987	0.0743390811
Regression	REGMISCALC	Regression	STAR10	True			.	.		.	.	.

In this table we see that the Root ASE of the tree model degrades a bit from training to validation but remains better than the network model at 0.204. The network model comes out at 0.27, degrading less than the tree model in validation but offering slightly worse performance. This pattern is duplicated in the misclassification rates, with the tree model dropping from 0.035 in training to 0.048 in validation, still better than the network model, which drops a touch from 0.072 in training to 0.074 in validation.

5.5 Conclusion

Dot dot dot.

6 Appendix

All code from this project is available in a Github repository at https://github.com/dchud/substar. In particular, the following scripts handle the tasks described:

Script	Task
github.com/dchud/substar/blob/master/fetch.py	Fetch all data about repositories
github.com/dchud/substar/blob/master/process.py	Process collected data into CSV file
github.com/dchud/substar/blob/master/combined-10000.txt	Extracted dataset, n=10,067